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Energy and Throughput Optimization of Wireless Mesh Networks with Continuous Power Control

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***Abstract*—Providing high data rates with minimum energy consumption is a crucial challenge for next generation wireless networks. There are few papers in the literature which combine these two issues. This paper focuses on multi-hop wireless mesh networks using a MAC layer based on S-TDMA (Spatial Time Division Multiple Access). We develop an optimization framework based on linear programming to study the relationship between throughput and energy consumption. Our contributions are two-fold. First, we formulate and solve, using column generation, a new MILP to compute offline energy-throughput tradeoff curve. We use a physical interference model where the nodes can perform continuous power control and can use a discrete set of data rates. Second, we highlight network engineering insights. We show, via numerical results, that power control and multi-rate functionalities allow optimal throughput to be reached, with lower energy consumption, using a mix of single hop and multi-hop routes.**

***Index Terms*—Mesh networks, throughput, energy consumption, scheduling, S-TDMA, energy-capacity tradeoff.**

I. Introduction

Providing users with high data rates, irrespective of their location, is a challenge for next generation cellular networks, like 3GPP LTE-Advanced and WIMAX. In this paper, we consider a managed wireless mesh network (WMN) organized in a tiered architecture: *i)* clients are connected to Mesh Routers (MR) and *ii)* a multi-hop wireless backhaul topology interconnects the MRs with the core network (Fig. 1). The MRs aggregate the uplink traffic generated by mobile clients and forward it through multi-hop communications to dedicated MRs, which are denoted gateways that bridge the backhaul network to the core network. Similarly, downlink traffic goes from the gateways to the MRs, then to the clients. We assume that mobile-to-MR and MR-to-MR traffic use independent frequencies. This work examines the backhaul network and does not take into account the users' requests, rather, their flows aggregated by the MRs. Optimizing the capacity of multi-hop wireless networks, defined as the maximum achievable total throughput in the network topology under a fairness criteria, has been a focus of research since the seminal work of Gupta and Kumar [1]. In addition, minimizing the energy expenditure and electromagnetic pollution of such infrastructures are also a socioeconomic challenge [2], [3]. Much work in the literature has studied how to maximize the capacity or how to minimize the energy consumption; however the work was done under strong assumptions and tradeoffs between achievable throughputs and energy have received very little attention.

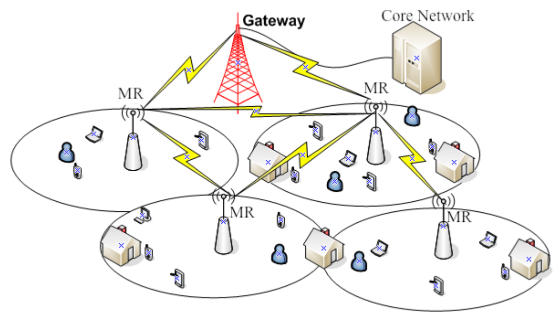

Fig. 1. Wireless mesh network architecture: mesh routers collect the traffic from clients (mobile or static) and forward it to the core network.

The first contribution of this work is to develop a flexible optimization framework, based on linear programming, to study multi-hop mesh networks. Several similar optimization tools have been proposed in the literature [4]–[6]. The main contribution of this framework is the modeling of continuous power control which provides fine-tuning of transmit power. The following features are also added by our work:

1) The routing is formulated as an edge-path multi-commodity flow. The routing, scheduling, and power allocation problems are jointly solved by a column generation algorithm. By computing a restricted set of decision variables, this algorithm solves reasonable size instances with a detailed modeling of the links.
2) The modeling of links relies on two concepts. *Logical links* efficiently represent routing over origin-destination pairs. The *physical link*, described by the parameters of the radio transmission, is used for physical layer issues. This combination of link models allows us to have a tractable formulation while using a detailed Signal-to-Noise-and-Interference-Ratio (SINR) interference model.

This framework is used to compute, offline, an optimal system setting of the backhaul network to minimize the energy consumption (resp. to maximize the capacity) under some network capacity (resp. energy consumption) requirements. A system setting corresponds to configuration parameters for operating the backhaul network, such as routing paths and scheduling, including the transmission power and rate assigned to each transmission. The impact of these mechanisms on the performances of the network, as well as the energy-throughput tradeoffs, are investigated in depth.

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Our second contribution is to provide practical engineering insights into WMN.

Our numerical results highlight that:

- Combining continuous power control and multi-rate functionalities allow the optimal achievable throughput to be reached with significantly lower energy consumption; in such tradeoffs some nodes actually use several combinations of power and rate at different times.
- The ratio of uplink over downlink traffic demands does not have a significant impact on the network capacity and energy consumption tradeoffs.
- In the case of fixed transmission power, single-hop communications are more energy efficient than multi-hop ones; in the case of continuous power control, it is the opposite.
- The clique area around the gateway plays a critical role in the energy-throughput tradeoff. The predominance of the clique in the capacity determination of a WMN has already been discussed in the literature. We obtain similar results concerning the energy-throughput tradeoff.

The rest of the paper is organized as follows. Section II reviews related work. Section III gives the problem statement and the network model. Then, in Section IV, we present our framework based on linear programming and column generation. Section V studies the energy-capacity tradeoff and demonstrates the benefits of continuous power control. In Section VI, we provide practical engineering insights into WMN. Finally, we conclude the paper in Section VII.

II. Related work

There exists a vast amount of literature devoted to improving the capacity of WMN and to minimizing energy consumption, even if these two areas are considered separately. To increase the throughput provided to nodes, several studies investigated TDMA scheduling techniques, i.e., to identify sets of links that can be simultaneously activated [4], [7]. Molle et al. [4] study the problem of routing and scheduling in IEEE 802.11 based networks. An optimization framework is provided for determining optimal routing and scheduling needed by the traffic in the network, considering a binary interference model and fixed transmission power. In a practical system, transmission power is an important tunable parameter to provide reliable and energy efficient communications: higher transmission power increases the SINR at the receiver to enable successful reception on a link, while lower transmission power mitigates interferences to other simultaneously utilized links. The joint problem of power control and scheduling link transmissions in wireless networks to optimize performance objectives (throughput, delay, energy) has received much attention in recent years [5], [8]–[10]. In [5], a joint scheduling, routing, and power control strategy is proposed. The authors develop a computational tool using column generation to maximize the minimum throughput among all flows. They highlight the usefulness of power control on the performance of multi-hop wireless networks. In this work, the power control is restricted to a small set of power levels. In [8], the problem of finding a minimum-length schedule that satisfies a set of specified traffic demands is addressed. It is shown that power control improves the spatial reuse, which leads to further improvements on the schedule length, compared to a fixed transmission power. Because scheduling with power control using a SINR model is NP-hard [7], [11], several papers have proposed heuristic algorithms to minimize the schedule length with and without power control [7], [12].
The optimization of energy consumption has also been extensively addressed in the literature. Typically, the energy expenditure in a node is linear with the transmission power [13]. From an energy efficiency standpoint, the most effective solution is to put the wireless nodes in sleep mode [14]. In order to produce an effective energy-efficient network, [15] proposed an optimization framework which allows for jointly computing a planning and energy management solution for WMN. The authors showed that the highest energy savings are achieved when network planning and management are handled simultaneously.

To the best of our knowledge, only a few papers investigated capacity and energy consumption jointly for WMN. Gorce et al. [16] studied energy, latency, and capacity tradeoff existing in multi-hop ad-hoc wireless networks. The authors assume a linear topology with a simple energy model. They proposed an analytical study that does not take into account a realistic interference model. The relation between energy minimization and throughput maximization for a 802.11 WLAN is analyzed in [17]. In [6], an optimization problems to study the max-min node lifetime and the max-min throughput of a multi-hop wireless network is formulated. The authors showed that the optimal tradeoffs between throughput and lifetime are usually not obtained at the minimum power that enables network connectivity. A multi-criteria optimization approach is proposed in [18] in order to study the relationship between energy consumption and throughput of multi-hop wireless networks. The authors tried to characterize and compute the Pareto front between these two issues using simple model and strong assumptions. In particular, they do not take into account the interferences among simultaneous transmissions and power control. Also the scheduling and the unfairness problems are not investigated.

Lopez-Peres et al. [19] investigated the problem of the joint allocation of Modulation and Coding Scheme (MCS), resource blocks, and power assignment to users in LTE cellular systems, while minimizing the overall power consumption. To achieve this objective, the authors break down the problem into two loops based on a linear program and a metaheuristic algorithm. They showed that to provide a minimum bit rate per user, it is better to use more resource blocks with lower MCS and less transmission power, than it is to use few resource blocks with higher MCS, but more power.

The lack of literature on both the capacity and energy consumption has lead to this in-depth study to investigate the tradeoff between them using a continuous power control.

III. Assumptions and Problem Definition

A. Assumptions and network properties

In this work, we consider a synchronized multi-hop single channel WMN where the MAC layer is based on S-

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TDMA. We are especially interested in broadband cellular networks like 3GPP LTE-Advanced and WIMAX. We assume a repeating transmission schedule of duration T (frame) that contains a fixed number of time-slots (whose lengths take on continuous values) allocated to nodes to transmit their traffic. To increase network efficiency, S-TDMA allows links with sufficient spatial separation to transmit simultaneously. One of our objectives is to compute an optimal S-TDMA scheduling that provides maximum throughput and efficient energy consumption.

We assume that the channel gains are quasi time-invariant. Under the assumption of quasi-static traffic and quasi time-invariant channel gains, it is reasonable to consider a static network. Each node is equipped with an omni-directional antenna. Its transmit power can be adjusted continuously at each transmission. Network capacity can be improved by increasing the number of gateways, if they are sufficiently spaced from each other [20]. In this paper, our scenarios are restricted to the single gateway case, though our models could address multi-gateway scenarios. We assume that there is an uplink flow from each MR to the gateway and a downlink flow from the gateway to each MR. These flows require several resources to be transmitted and are routed through multi-hop paths to be computed (see Fig. 1).

B. Network model and notations

A wireless mesh network is a fixed infrastructure that consists of a set V of nodes composed of a set of mesh routers, denoted $\mathrm{V_{MR}}$, and a gateway Gw. This section is dedicated to the modeling of the WMN.

1) Node model: Each mesh router is characterized by its identity $u \in \mathrm{V_{MR}}$, its geographic position, and a weight $d_{UL}(u)$ (resp. $d_{DL}(u)$) that reflects its uplink (resp. downlink) throughput requirement. The uplink throughput requirement is needed to forward the uplink traffic generated by mobile clients to the gateway.

During each time slot, a node can be either idle, receiving, or transmitting. When transmitting, the transmit power of the node u is denoted $P_t(u)$ and is bounded by a maximum value P_{max}. The nodes have a continuous power control capability in order to reduce the interferences and to use the appropriate transmission rate, as is explained in the following section. The energy consumption of a node, which depends on its activity, as detailed in Section III-C2, is denoted $J(u)$.

In the following, we present the modeling of the links by introducing an aggregated notion of *logical links* and a more detailed notion of *physical links*. The former completes, with V, a graph representation of the network, which is convenient for computing optimal routings. The latter describes all the parameters of a transmission needed for computing capacity and energy efficient resource allocations.

2) Links and SINR interference model: When a communication occurs between two nodes, traffic is sent over the link at a rate r which belongs to a set of transmission rate $R = \{r_j\}$, $N_r = |R|$, $0 < r_1 < r_2 < ... < r_{N_r}$. Note that each transmission rate r_j is the result of the use of a modulation and coding scheme MCS_j. We introduce two notions of (directed) links. Let us denote a *logical link* $e = (u, v)$ identified only by an origin-destination pair. E is the set of feasible logical links and $G = (V, E)$ is the graph representation of the WMN. Such a representation is convenient for efficiently handling routing. However, to assess the achievability of a logical link and hence to define E and cope with interference and energy issues, a more detailed notion of a link is required. Let us denote a *physical link* by l, identified by the following parameters (e, P_t, r).

- $e = (o(l), d(l)) \in E$ the logical link between the origin-destination pair $(o(l), d(l))$.
- $P_t \in [0, P_{max}]$: the transmit power of the node $o(l)$ during this communication.
- $r \in R$: the transmission rate, in bits per second, used during this communication.

Each rate r has a corresponding SINR requirement $\beta(r)$ for communication to be established with some given parameters, such as a maximum bit error rate ($\beta(r_i) > \beta(r_{i-1})$). This means that a physical link $l = (e, P_t, r)$ is established if and only if the power received from $o(l)$ in $d(l)$ is enough to reach the SINR requirement of rate r. The power received at $d(l)$ is proportional to P_t and to the channel gain function, denoted $G(l)$, which takes into account a given radio propagation model (path loss, fading, and shadowing). Altogether, the SINR condition at receiver $d(l)$, in the presence of a set s of other simultaneously active transmissions, is expressed as follows:

$$SINR_{d(l)} = \frac{P_t * G(o(l), d(l))}{\mu + \sum\limits_{l'=(e',P'_t,r') \neq l, l' \in s} P'_t * G(o(l'), d(l))} \geq \beta(r), \tag{1}$$

where $\mu \in \mathbb{R}^+$ represents the thermal noise at the receiver.

The set of feasible physical links is denoted $\mathcal{L}$ and a logical link e exists if and only if there exists $P_t \in [0, P_{max}]$ such that $l = (e, P_t, r_1) \in \mathcal{L}$. The set of logical links can therefore be defined as $E = \{e = (u, v), \exists P_t < P_{max}, (e, P_t, r_1) \in \mathcal{L}\}$. Note that $\mathcal{L}$ is infinite, while E is finite and tractable for routing issues.

TABLE I
NETWORK MODEL PARAMETERS AND NOTATIONS

E, $\mathcal{L}$	Set of logical and physical links
Gw, $\mathrm{V_{MR}}$	Gateway and set of mesh routers
μ, $\beta(.)$	Thermal noise and SINR threshold function
$G(.)$	Channel gain function
$P_t(.)$	Transmit power
$P_r(.)$	Power consumed by the receiver
$d_{UL(.)}, d_{DL(.)}$	Resp. Uplink and Downlink weight
I	An ISet
$\mathcal{I}$	Set of all possible ISets
R, N_r	Set of available rates: $R = \{\mathrm{r_j}\}$, $\lvert R\rvert = N_r$
Cc	Constant power consumption

3) Conflict free scheduling: A set I of physical links $(l^1, l^2, ..., l^n)$ is said to be an *independent set* (*ISet*) if and only if Eq. (1) holds at all receivers and $\forall l^i, l^j \in s$, $i \neq j$, $o(l^i) \neq o(l^j)$, $d(l^i) \neq d(l^j)$ and $o(l^i) \neq d(l^j)$. All links in this set can be scheduled at the same time without creating

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any decoding conflict. The set of all possible *ISets* is denoted $\mathcal{I}$.

Note that, because we consider continuous power control, the set of physical links is infinite. However $\mathcal{I}$ can be reduced to a finite set of "minimal ISets" with respect to transmission powers: we only consider ISets in which transmission power cannot be reduced without modifying the transmission rate of links. This does not provide a tractable and easily generated set of ISets; however, column generation allows for generating only a subset of useful ISets (this will be discussed in details in Section IV-B).

By scheduling only ISets, we ensure that the schedule is conflict free. Let $w(\mathrm{I})$ be the time allocated to the ISet I, we have $\sum_{I\in\mathcal{I}} w(\mathrm{I}) = T$. Our optimization problems will compute the $w(\mathrm{I})$'s to maximize the objective function.

4) Routing model: The activation of an ISet I provides to each logical link, $e \in E$, a rate $r_e(\mathrm{I})$ equal to $r(l) \in R$ if it exists $l = (e, P_t(l), r(l)) \in \mathrm{I}$, and to 0, otherwise. Hence, each logical link e sees a total rate equal to $\sum_{\mathrm{I}\in\mathcal{I}} r_e(\mathrm{I})w(\mathrm{I})$. These rates are used to route the traffic between the mesh routers and the gateway. We define a routing path as a set of logical links through intermediate nodes from source to destination. For each mesh router $u \in \mathrm{V_{MR}}$, let $\mathcal{P}^u_{UL}$ (resp. $\mathcal{P}^u_{DL}$) denote the set of uplink (resp. downlink) paths between u and the gateway, and let $\mathcal{P}_{UL} = \cup_u \mathcal{P}^u_{UL}$ (resp. $\mathcal{P}_{DL} = \cup_u \mathcal{P}^u_{DL}$) denote the set of uplink (resp. downlink) paths in the network. The uplink traffic is modeled by the flow function $f_{UL} : \mathcal{P}_{UL} \to \mathbb{R}^+$. The traffic sent by u is hence $\sum_{\mathrm{P}\in\mathcal{P}^u_{UL}} f_{UL}(\mathrm{P})$ (as it is for the downlink traffic flow). The flow over a logical link e is the sum of the uplink and downlink traffic on the paths going through e. This flow has to be below the total rate of e. The problem of routing is to calculate the flow function that maximizes the throughput or minimizes the energy consumption.

C. Network capacity and energy consumption model

1) Network capacity: we assume that the throughput requirements of the mesh routers are heterogeneous. This can be explained by the number of clients connected to each mesh router. To model this, each mesh router is allocated a weight that reflects its greedy throughput requirement with respect to a common base λ. We consider a fair notion of network capacity in which every router receives at least its weighted share of the global throughput. The resources are therefore assigned so that each node $u \in V$ receives an end-to-end uplink throughput $\lambda_{UL}(u)$ (resp. downlink $\lambda_{DL}(u)$), so that : $\lambda_{UL}(u) \geq d_{UL}(u) * \lambda$, where $d_{UL}(u)$ (resp. $d_{DL}(u)$) is the uplink (resp. downlink) weight of node u and λ is the common base throughput (in bps) to be optimized. Hence, the network capacity is at least $\sum\limits_{u\in V_{MR}} (\lambda_{DL}(u)+\lambda_{UL}(u)) \geq \sum\limits_{u\in V_{MR}} d_u * \lambda$, where $d_u = d_{UL}(u) + d_{DL}(u)$. Maximizing λ achieves a fair maximization of the network capacity.

The idea behind throughput-optimal scheduling is to schedule as many links as possible in each time slot, that is, to maximize the spatial reuse of system resources. This objective has to be mitigated with interferences and energy consumption constraints.

2) Energy consumption model: We propose a generic energy consumption model that is based on node activity (idle, transmission, reception)[1]. A node can be operational or non-operational. When the radio part of the node is not in operation, some components are always on (due to signal processing, battery backup, as well as site cooling) and those components consume a given quantity of power, denoted Cc. This state is called an *Idle State*. When the radio part is operational, the node u can either be in *Transmission State* ($u = o(l)$) or in *Reception State* ($u = d(l)$) and it consumes, respectively, $(Cc + a(u) * P_t(o(l)))$ and $(Cc + P_r(u))$. The coefficient $a(u)$ accounts for the power consumption that scales with the average radiated power (due to the high power consumption of the amplifier). Here, we assume that $P_r(u)$ is fixed for all nodes. The relation between transmission power and node energy consumption is nearly linear [13]; see Fig. 2. The fixed cost Cc is consumed regardless of the state of the nodes. Note that our optimization problem, detailed in Section IV, does not depend on this parameter since it is static and consumed independently of node state. To reduce energy consumption, it is possible to turn off a node (Sleep State) when it is not in operation. This approach is studied in several papers and is not investigated in this work. Each ISet I has power consumption (Watts), $J(\mathrm{I})$, which is calculated as follows:

$$J(\mathrm{I}) = |V| * Cc + \sum_{l\in\mathrm{I}} a(o(l)) * P_t(o(l)) + \sum_{l\in\mathrm{I}} P_r(d(l)) \qquad (2)$$

The total energy consumption of the network, during the frame length T, is $\sum_{\mathrm{I}\in\mathcal{I}} w(\mathrm{I})J(\mathrm{I})$ when the scheduling is done using the $w(\mathrm{I})$'s.

Table I summarizes all the network model parameters and notations.

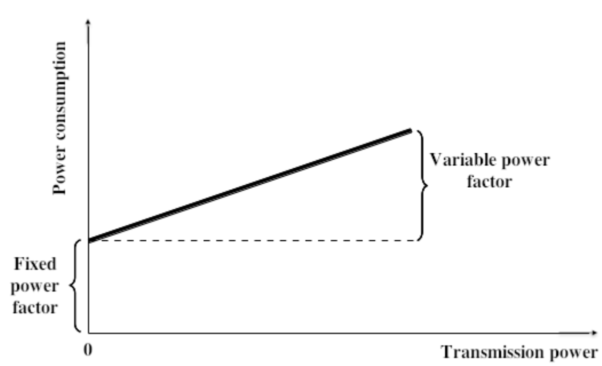

Fig. 2. Illustration of the power consumption model

In the next section we formulate two different linear programming problems: the first maximizes the network capacity subject to a constraint on the total energy consumption, while the second minimizes the total energy consumption subject to a capacity constraint. We also present the column generation

[1]Our model is based on the model proposed in the EARTH project [13].

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algorithm that we use to cope with the combinatorial complexity of the paths and the set of ISets.

IV. Linear Models for Capacity and Energy Consumption Optimizations

A. Master formulation

The joint routing and scheduling problem can be expressed in two linear programs (LP) depending on the objective. The first one maximizes the capacity with an energy budget constraint. The Master Problem to Maximize Capacity (MPMC) is formulated as follows:

$$\max_{\lambda,(w(I))_{I\in\mathcal{I}},f_{UL}(u)_{u\in V},f_{DL}(u)_{u\in V}} \lambda$$

$$\text{subject to } \forall u \in V_{MR} \quad \sum_{\mathrm{P}\in\mathcal{P}^u_{UL}} f_{UL}(\mathrm{P}) \geq d_{UL}(u) * \lambda \tag{3}$$

$$\forall u \in V_{MR} \quad \sum_{\mathrm{P}\in\mathcal{P}^u_{DL}} f_{DL}(\mathrm{P}) \geq d_{DL}(u) * \lambda \tag{4}$$

$$\forall e \in E \quad T * \Big(\sum_{\mathrm{P}\in\mathcal{P}_{DL},\mathrm{P}\ni e} f_{DL}(\mathrm{P}) + \sum_{\mathrm{P}\in\mathcal{P}_{UL},\mathrm{P}\ni e} f_{UL}(\mathrm{P}) \Big) \leq \sum_{\mathrm{I}\in\mathcal{I}} r_e(\mathrm{I}) w(\mathrm{I}) \tag{5}$$

$$\sum_{\mathrm{I}\in\mathcal{I}} w(\mathrm{I}) \leq T \tag{6}$$

$$\sum_{\mathrm{I}\in\mathcal{I}} w(\mathrm{I}) J(\mathrm{I}) \leq E_M \tag{7}$$

$$\lambda > 0, \quad (w(I))_{I\in\mathcal{I}} \geq 0, \quad f_{UL}(u)_{u\in V} \geq 0, \quad f_{DL}(u)_{u\in V} \geq 0 \tag{8}$$

The objective function imposes the maximization of the end-to-end base throughput λ. Equations (3)-(5) express the routing part as flows between the MRs and the gateway. Constraints (5) impose that the total traffic on the logical link e should not exceed the capacity of the link itself while constraints (3) (resp. (4)) ensure that each MR achieves a maximum uplink (resp. downlink) throughput, taking into account the nodes weights. Eq. (7) constrains the total energy expenditure of the network to a budget E_M.

The second LP formulation minimizes the total energy expenditure under a capacity guarantee and is called the Master Problem to Minimize Energy consumption (MPME):

$$\min_{\lambda,(w(I))_{I\in\mathcal{I}},f_{UL}(u)_{u\in V},f_{DL}(u)_{u\in V}} \sum_{\mathrm{I}\in\mathcal{I}} w(\mathrm{I}) J(\mathrm{I})$$

subject to Equations (3)-(6) and

$$\lambda \geq \lambda_{min} \tag{9}$$

The flow equations of MPME remain the same as Eq. (3)-(5) while the upper bound on the energy consumption (Eq. (7)) is replaced by a lower bound on the network capacity (Eq. (9)). Finally, the objective is to minimize the energy expenditure of the network.

The physical link parameters (such as the transmission power and the link rate) are explicitly taken into account by each ISet $\mathrm{I} \in \mathcal{I}$: recall that an ISet is a set of physical links and will be calculated by a mixed integer linear program, detailed as follows.

The MPMC and MPME formulations allow us to calculate the Pareto front between the network capacity and the energy consumption. Fig. 3 explains how we calculate this Pareto front. The first step is to calculate the two extremal points, $P0 = (E_{min}, \lambda_{min})$ and $P1 = (E_{max}, \lambda_{max})$, which present the minimum energy consumption, E_{min}, and the maximum base throughput λ_{max}. Recall that the network capacity is equal to $\sum_v d_v * \lambda$. $P0$ and $P1$ are calculated as follows:

$$P0 \begin{cases} E_{min} = \min \sum_{\mathrm{I}\in\mathcal{I}} w(\mathrm{I}) J(\mathrm{I}) \quad | \quad \lambda > 0 \quad (using \quad MPMC) \\ \lambda_{min} = \max \lambda \quad | \quad \sum_{\mathrm{I}\in\mathcal{I}} w(\mathrm{I}) J(\mathrm{I}) \leq J_{min} \quad (MPME) \end{cases}$$

$$P1 \begin{cases} \lambda_{max} = \max \lambda \quad | \quad \sum_{\mathrm{I}\in\mathcal{I}} w(\mathrm{I}) J(\mathrm{I}) \leq \infty \quad (MPMC) \\ E_{max} = \min \sum_{\mathrm{I}\in\mathcal{I}} w(\mathrm{I}) J(\mathrm{I}) \quad | \quad \lambda \geq \lambda_{max} \quad (MPME) \end{cases}$$

Once the two extremal points have been determined, we use one of the two linear programs to plot the rest of the curve. For example, if we use the MPMC linear program, then we vary E_M between E_{min} and E_{max}. This curve has several properties. In particular, (i) the throughput is a strictly increasing function for $E \in [E_{min}, E_{max}]$, (ii) for each $E_M \in [E_{min}, E_{max}]$ there exists a saturation throughput λ_m such that $\lambda(E_M) = \lambda_m$ and $\lambda(E) < \lambda_m$ for $E < E_M$ [18].

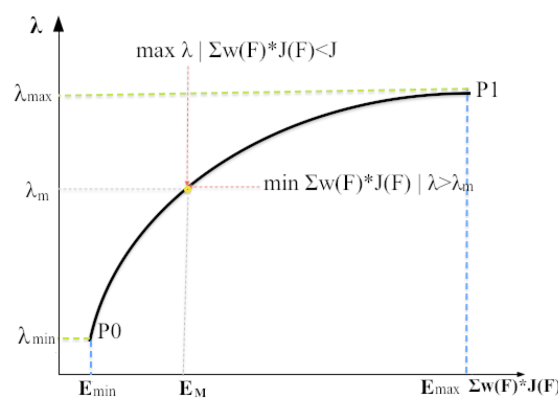

Fig. 3. The Front Pareto description.

Because the number of variables (paths and ISets) are exponential with the size of the network, these formulations are not scalable as such. However, most of them will not be used in an optimal solution. Therefore, it is not practical to generate all the variables. Column generation [4], [5] is a prominent and efficient technique to cope with this situation. Based on linear programming duality results, it avoids the complete enumeration of the variable sets.

B. Column generation

Column generation is an algorithmic technique for solving linear programs with an exponential set of variables, which

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TABLE II
LP MODEL NOTATIONS

$J(\mathrm{I})$	Total power consumption of ISet I
$w(\mathrm{I})$	Time allocated to ISet I
$\mathrm{P_{UL}}$, $\mathrm{P_{DL}}$	Resp. UL and DL Path
$\mathrm{f_{UL}(P)}$, $\mathrm{f_{DL}(P)}$	Resp. UL and DL Flow of path P
E_M	Energy budget
λ_{min}	Minimum throughput requirement
$\theta_{UL}(.), \gamma(.), \sigma$	Dual variables
n	Number of nodes

takes its roots in duality theory [21]. Each linear program, denoted *master* in this context, has an associated and unique *dual* program. For each constraint of the master, there is a dual variable that is defined. Similarly, for each variable of the master, there is a constraint in the dual, which binds the dual variables related to the master constraints in which the concerned master variable appears. This is done in such a way that the duality association is reflexive (the dual of the dual of a LP is the original LP). The dual formulations of MPMC are detailed in the following section. Each instantiation of the master variables is similarly associated to an instantiation of the dual variables, such that the master values represent a sub-optimal feasible solution if and only if the dual values are a non feasible solution, i.e., that at least one constraint of the dual is violated. Both sets of master and dual values represent a feasible solution if and only if they are both optimal (with the property that the master and dual optimal objectives values are the same).

Exploiting this property, the column generation principle involves first solving the master on a restricted set of variables (also called columns, hence the column generation), considering that the non considered variables are zero. In our case, the variables are the flow over the paths and the weights of the ISets. We then consider a restricted set of paths $\mathcal{P}_0$ and ISets $\mathcal{I}_0$ which have to be carefully chosen to ensure the existence of an initial feasible solution. Generally, $\mathcal{P}_0$ contains a shortest path between each mesh router and the gateway (uplink/downlink paths), and $\mathcal{I}_0 = \{\{l = (\mathrm{e}, P_t, r_1)\}, \mathrm{e} \in \mathrm{E}, P_t = \frac{\beta(r_1)*\mu}{G(l)}\}$.

Thus, the solving of the master on this restricted set of variables is fast and, if there exists a feasible solution, it is related to a set of dual values. If the master solution is suboptimal, the aforementioned property of the duality claims that what the dual values describe is a non feasible solution of the dual. There is, then, at least one constraint of the dual that is violated and which is in bijection with a variable of the master, which is here a path or an ISet. The separation theorem claims that solving the master problem on the set of variables, including this new variable, will improve the solution [21]. The process loops until no such variable exists, as depicted in Fig. 4. When this state has been reached, the dual variables represent a feasible solution. Since the master also does, the theory of duality claims that both the master and the dual are optimal. Finding the new variables in the column generation process consists of solving the auxiliary programs described in Section IV-B2.

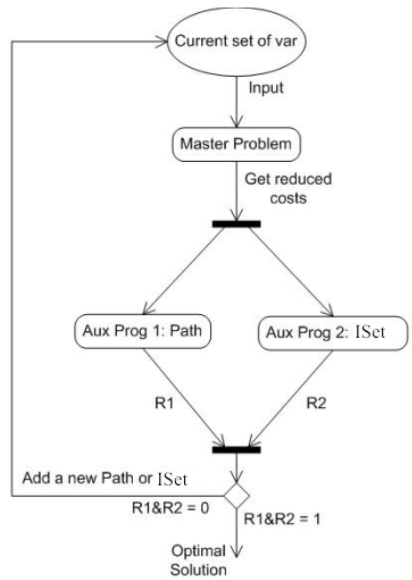

Fig. 4. The column generation process

1) Dual formulation: Below, we present the dual formulation of MPMC. Note that the one for MPME is very similar. Recall that in this LP, there is a constraint for each variable of the master, be it the flow on a path or the weighting of an ISet. We denote $\theta_{UL}(.)$, $\theta_{DL}(.)$, $\gamma(.)$, Ω, and σ, respectively, to be the dual variables associated to constraints (3), (4), (5), (6) and (7). $\mathrm{o(P)}$ denotes the source node of path P. $J(u)$ is the power consumption (Watts) of node u:

$$\min_{(\theta_{UL}(u))_{u\in V},(\theta_{DL}(u))_{u\in V},\sigma,\Omega,(\gamma(e))_{e\in E}} \quad T*\Omega + E_M*\sigma$$

$$\text{subject to:} \quad \forall \mathrm{P} \in \mathcal{P}_{UL} \quad \theta_{UL}(\mathrm{o(P)}) \leq T*\sum_{e\in \mathrm{P}} \gamma(e) \quad (10)$$

$$\forall \mathrm{P} \in \mathcal{P}_{DL} \quad \theta_{DL}(\mathrm{o(P)}) \leq T*\sum_{e\in \mathrm{P}} \gamma(e) \quad (11)$$

$$\mathrm{I} \in \mathcal{I} \quad \sum_{e\in E} r_e(\mathrm{I})\gamma(e) - \sigma J(\mathrm{I}) - \Omega \leq 0 \quad (12)$$

$$\sum_{u\in V_{MR}} (\theta_{UL}(u)d(u) + \theta_{DL}(u)d(u)) \geq 1 \quad (13)$$

2) Auxiliary programs: We now describe the two auxiliary programs which determine if there are uplink/downlink paths or ISets that violate the constraints of the dual program. The first program, associated to constraints Eq. (10)-(11), finds, for each source node, a weighted path with a weight lower than the dual variable associated to the source node. If the minimum weighted path fits the constraint, then so do all other paths. This problem is similar to the shortest path problem; hence, it can be easily solved using linear programming (LP). This LP minimizes the weighted path with $\gamma(e)$ under a conservation flow constraint, which defines the relation between incoming traffic and outgoing traffic for each node [22].

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The second auxiliary problem is associated with constraint Eq. (12). It is necessary to decide if there exists an ISet I such that $\sum_{e \in E} r_e \gamma(e) - \sigma J(\mathrm{I}) - \Omega > 0$. Again, if the maximum weight communication set respects Eq. (12), then so do all other ISets. Our auxiliary program considers two scenarios:

a) Generation of ISets with continuous power control and multi-rate: In this case, each node continuously controls its transmission power and chooses the best MCS (or rate $r \in R$), depending on the SINR achieved at the receiver. Given a set of dual variables ($\gamma(.)$, σ) obtained from the master problem (MPME or MPMC), we generate a new ISet by solving the following Mixed Integer Linear Program:

$$\max_{\Psi, P_t, J} \sum_{e \in E} (r_e \gamma(e)) - \sigma \sum_{u \in V} J(u) - \Omega \tag{14}$$

$$\forall u \in V \qquad J(u) \geq a(u) * P_t(u) + \sum_{v \in V} \sum_{1 \leq i \leq N_r} P_r(u) \Psi^i_{(v,u)} + Cc \tag{15}$$

$$\forall (u,v) \in E, i \in [1, N_r] \qquad P_t(u) * G(u,v) \geq \beta(r_i) * \left(\sum_{u' \neq u,v} P_t(u') * G(u',v) + \mu \right) - \left(1 - \Psi^i_{(u,v)}\right) n * P_{max} \tag{16}$$

$$\forall u \in V \qquad \sum_{v \in V} \sum_{1 \leq i \leq N_r} \Psi^i_{(u,v)} + \sum_{w \in V} \sum_{1 \leq i \leq N_r} \Psi^i_{(w,u)} \leq 1 \tag{17}$$

$$\forall e = (u,v) \in E \qquad r_e = \sum_{1 \leq i \leq N_r} r_i \Psi^i_{(u,v)} \tag{18}$$

$$\forall u \in V \qquad P_t(u) \leq P_{max} \tag{19}$$

The decision variables of this linear program are $P_t(u)$, $J(u)$ and $\Psi^i_{(u,v)}$ where $(u,v) \in E$ and $i \in [1, N_r]$. The binary variable $\Psi^i_{(u,v)}$ is equal to 1 if the communication between u and v is active in the new ISet, with a transmission rate of at least r_i, and to 0 otherwise. The goal is to find a new ISet I where $(\sum_{e \in E} r_e \gamma(e) - \sigma \sum_{u \in V} J(u))$ is maximum (Eq. (14)). If this ISet violates Eq. (12), it may improve the solution of the master program. If not, no other ISet can, either, do and the solution of the master is optimal. The constraints of this ILP define the ISet structure as follows. The energy consumption model, detailed in Subsection III-C2, is presented by constraints (15). The constraint (16) ensures that the SINR condition is satisfied for all active links in the ISet, taking into account the transmission rate used by each one. Note that $(1 - \Psi^i_{(u,v)}) n * P_{max}$ equals 0 when the link (u,v) is active, hence the constraint (16) reverts back to the classical interference constraint (1). Otherwise ($\Psi^i_{(u,v)} = 0$), and $n * P_{max}$ ensures that $P_t(u)$ can be equal to 0 (constraint (16) is always respected), where n is the number of nodes. Finally, constraint (17) implies that each node is active in at most one link with one transmission rate in each time-slot. This constraint also ensures the half-duplex property where a node cannot transmit and receive simultaneously.

This auxiliary program builds a new ISet I which contains the following physical links: for all $e = (u,v) \in E$ such that $\Psi^i_{(u,v)} = 1$, $l = (e, P_t(u), r_i) \in I$.

b) Generation of ISets with single-rate: In this case, we assume that only a single rate, $r \in R$, is available and that each node can continuously control its transmission power. We study this case using the previous auxiliary program by setting $N_r = 1$.

We have presented our linear programs, to optimize network capacity and energy consumption, and have presented the column generation to solve them. Next, we will discuss the energy-capacity tradeoff. We calculate an optimal system setting of the network to minimize the energy consumption (resp. to maximize the capacity) under the requirements of high network capacity (resp. low energy consumption).

V. SINR BASED MODEL: CONTINUOUS POWER CONTROL AND SINGLE-RATE

In this section, we assume that each node operates at a fixed transmission rate (fixed MCS) and can tune its transmission power at each transmission. We calculate optimal routes for data, transmission power, resources allocation, and link schedules.

A. Scenarios and Model Parameters

Both the capacity-oriented and energy-oriented formulations and the column generation algorithm are implemented and tested using AMPL/CPLEX [23], [24]. In all of our numerical results, we consider a multi-hop WMN with regular and random topologies. The regular network topology has its nodes positioned on a grid. The random topologies are generated with a Poisson process in the Euclidean plane. In all of our scenarios, we consider 24 MRs deployed in an area of 500m*500m and a gateway located in the center. Except when otherwise stated, all MRs have the same throughput requirement (the impact of a non-uniform throughput requirement is investigated in Subsection VI-B). The path-loss attenuation is equal to $(\frac{d(u,v)}{d_0})^{-\alpha}$ where $\alpha = 3.6$ is the path loss exponent and $d_0 = 1m$ is the near-field crossover distance. The noise power density is -174 dBm/Hz. We consider five MCSs, presented in Table III, available to each node. The numerical values of the energy consumption model are adapted from the models of the EARTH project for small cells [2]. Combining equations (2) and (6), the energy cost obtained is $Cc{*}|V|$ plus the variable part of the energy cost which does not depend on Cc. Indeed, the fixed cost of circuit consumption has no impact on the optimization of the transmit power assignment and therefore can be considered as null in the following, up to a constant shift of the numerical results. Table IV summarizes all physical parameters.

B. Capacity and energy tradeoff in the case of 1 MCS

1) Insensitivity of the mix of UL/DL traffic to the energy-capacity tradeoff: the Pareto front of the capacity/energy tradeoff is depicted in Fig. 5 for a grid and a random network using only MCS4 with continuous power control. In this study, we consider three scenarios: uplink-only, downlink-only and

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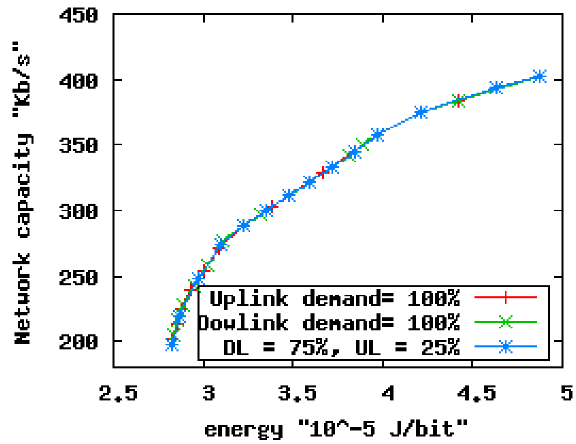
TABLE III
MODULATION AND CODING SCHEMES: MCS [19]

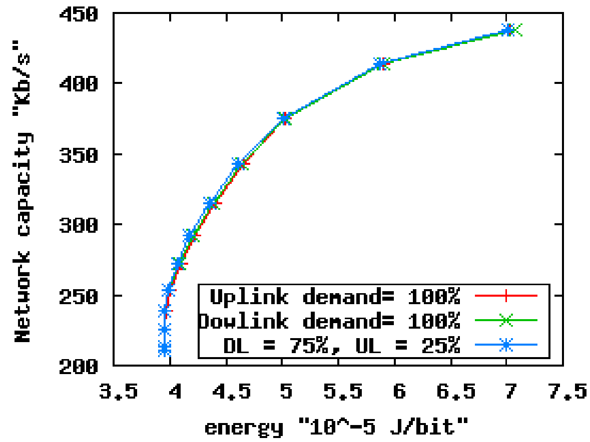
MCS	Modulation	CR	$\beta[dB]$	Throughput	Efficiency
MCS1	QPSK	1/2	1	164 Kb/s	0.933 b/s/Hz
MCS2	16QAM	1/2	10	328.12 Kb/s	1.866 b/s/Hz
MCS3	16QAM	3/5	11.40	393.75 Kb/s	2.24 b/s/Hz
MCS4	64QAM	1/2	11.80	492.18 Kb/s	2.8 b/s/Hz
MCS5	64QAM	3/5	13.80	590.625 Kb/s	3.36 b/s/Hz

TABLE IV
PHYSICAL LAYER PARAMETERS

Noise power density	-174 dBm/Hz
Scheduling block size	1ms/180 Khz
$Path-lossfunction$	$(\frac{d(u,v)}{d_0})^{-\alpha}$, $\alpha = 3.6, d_0 = 1m$
Maximum transmit power (P_{max})	30dBm
Antenna gain	5dBi
Amplifier coefficient (a)	10
Power consumed by the receiver (P_r)	0.5Watt



(a) Multi-hop grid network



(b) Multi-hop random network

Fig. 5. Capacity and energy tradeoff, using MCS4 and $P_{max} = 15dBm$, in the case of uplink-only, downlink-only and mixed traffic (25% uplink + 75% downlink).

mixed traffic with 25% uplink and 75% downlink. In each case, a minimal energy budget for the network is required to route all traffic between the MRs and the gateway. We observe that there is no significant impact from the mix of uplink and downlink flows on the energy-capacity tradeoffs. In fact, the capacity is constrained by the activity inside a bottleneck zone around the gateway [20], [25]. In this area, there is no spatial reuse as only one link can be activated at each time, either in uplink or in downlink. Hence, the network capacity cannot be improved by combining the uplink and downlink flows. Note that the uplink and downlink flows paths are not necessarily the same, as the ISets are different due to the asymmetric interferences.

2) Impact of maximum power transmission on energy-capacity tradeoff: Fig. 6 depicts the energy-capacity Pareto fronts on a multi-hop random topology, when the maximum power transmission takes one of three values (10dBm, 15dBm and 21dBm). It shows that increasing the maximum transmission power increases the magnitude of the energy-capacity tradeoff and the maximum network capacity. It also shows that a larger network capacity, with the same energy expenditure, can be achieved. Indeed, higher transmission power induces, first, a higher connectivity in the network, in particular around the gateway. Intuitively, in the bottleneck area, going directly to the gateway saves time, which significantly increases the capacity. Second, new ISets can be generated with better spatial reuse and with the same energy budget constraint. However, increasing transmission power is a major contributor to increasing energy consumption, which explains increasing numbers of the energy-capacity tradeoff solutions.

3) Benifit due to power control: The benifit of enabling continuous power control is illustrated in Fig. 7(a) and Fig. 7(b) which present, respectively, network capacity and energy consumption in the cases of power control and of fixed power[2]. Each result is averaged on 15 random instances. Let P_{1hop} be the transmission power which allows all MRs to communicate directly with the gateway. Fig. 7(a) shows that when $P_{max} < P_{1hop}$, the use of continuous power control is very beneficial for increasing network capacity and energy consumption. The transmit power is adjusted to reduce the interferences, which increases the spatial reuse and thus improves the throughput. When $P_{max} \geq P_{1hop}$, continuous power control and fixed power leads to the same network capacity. In the case of fixed power, this capacity is obtained with high transmission power and, hence, with high energy consumption. Interestingly, power control allows this capacity to be achieved with multi-hop communications and lower transmission power, which provides about 70% of energy gain. Moreover, the average gain in network capacity reaches about 25%, and the energy gain is between 25% and 70%. It is important to note that, in the case of power control, the energy consumption increases only if the network capacity increases.

[2]All nodes transmit at the maximum transmission power

VI. MULTI-RATE TRANSMISSION AND OPTIMAL SYSTEM SETTING

Given an ISet I, each link $l = (u, v, P_t, r) \in$ I is activated during w(I) with the transmission rate $r(l) \in R$. An optimal system setting consists of finding, for each communication, the best MCS_j with a transmission power that minimizes

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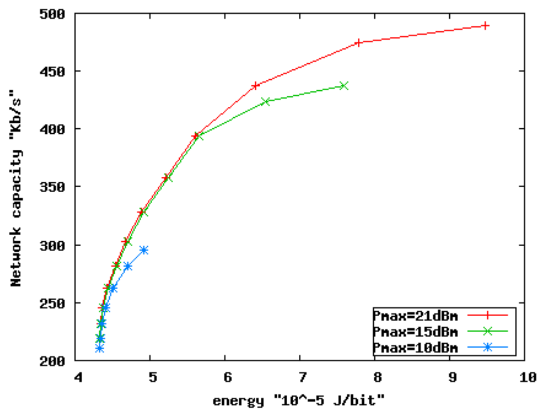


Fig. 6. Impact of maximum power transmission on energy-capacity tradeoff: random network with MCS4.

TABLE V
MCS VS ENERGY CONSUMPTION PER BIT/S (J/BIT/S)

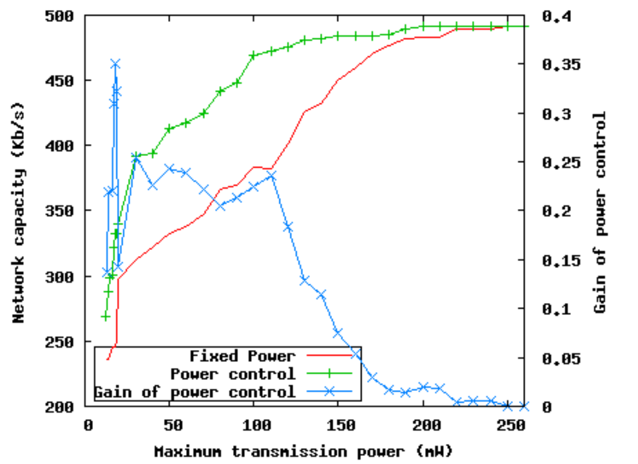
MCS	Energy consumption per bit/s
MCS1	2.43 10^{-8} J/bit/s
MCS2	4.82 10^{-8} J/bit/s
MCS3	4.61 10^{-8} J/bit/s
MCS4	3.2 10^{-8} J/bit/s
MCS5	3.57 10^{-8} J/bit/s

the overall energy consumption and maximizes the network capacity. The main question to be addressed is how $MCSs$ and power should be allocated to each transmission. In this section, we consider the five MCS presented in Table III. Note that energy consumption and capacity are linked to the MCS used. Intuitively, higher modulation means higher throughput and capacity, but requires greater transmission power to meet the SINR threshold constraint. This increases the tradeoff between capacity and energy consumption.

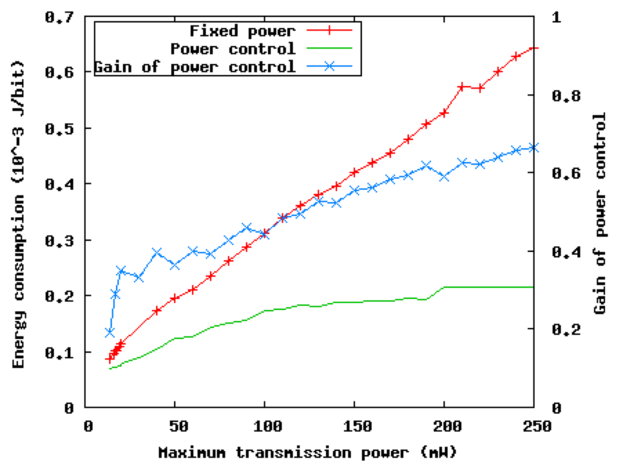
To further illustrate this tradeoff, a simple scenario of a single communication between a source and destination is shown. The energy consumption per bit per second (J/bit/s) for each transmission rate (or MCS) is depicted in Table V. We observe that MCS1 is the most energy efficient; however, it is the lowest in terms of throughput, while MCS5 leads to higher throughput.

In this scenario, with an isolated link, transmitting power and throughput are bounded by the MCS characteristics which result in a tradeoff on the energy efficiency. As seen in Section V, in an example situation with several nodes and concurrent communications, the interferences and the spatial reuse induce a tradeoff between the overall energy consumption and capacity. In the following section, we study the tradeoff in a network when the nodes perform continuous power control and use multi-rate transmission.

Next, we assume that the MCS presented in Table III are available for each node. For each network, an optimal solution is calculated including: network capacity, energy consumption, routing, resource allocation, physical parameters of each node (transmit power and MCS used for each transmission), and activation time of each communication.



(a) Network capacity



(b) Energy consumption

Fig. 7. The impact of maximum transmission power and benifit due to power control: each result is averaged on 15 random instances using MCS4

A. Energy and Capacity Tradeoff

To reduce complexity and computing time, without loss of generality, we eliminate the MCS1 (which dramatically increases the number of available links and leads to prohibitive computation times) and use only the four other MCSs. The tradeoff between energy consumption and network capacity is depicted in Fig. 8, which presents the fixed power case and the continuous power control case. This figure shows an important tradeoff between capacity and energy consumption. This tradeoff results from the use of different MCS and from the impact of spatial reuse. In the control power case, activating only one link on each time-slot with the lowest MCS is the most energy efficient solution. This is, of course, at the cost of achieving the worst network capacity: increasing the number of simultaneous communications and using high modulations increases the capacity but consumes more energy.

Comparing the energy-capacity tradeoff obtained with the two scenarios emphasizes that continuous power control increases the magnitude of the tradeoff (the capacity varies between 140 and 450 Kb/s), and allows higher network capacity to be achieved with lower energy consumption.

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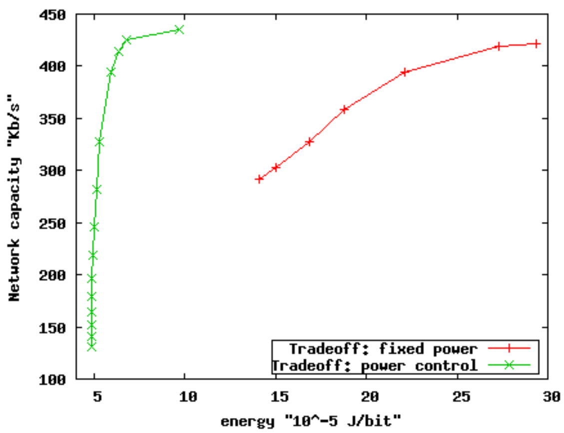


Fig. 8. The energy and capacity tradeoff: fixed power vs continuous power control (random network and multi-rate transmission)

B. *Impact of topology and throughput requirement*

Most of the previous results were obtained with a single random network and homogeneous throughput requirement. We investigate the impact of the throughput requirement distribution (represented by the weight d_u) and the topology on the energy-capacity tradeoff.

1) Impact of topology: In Fig. 9, we illlustrate the energy-capacity tradeoff according to a selection of seven random topologies. Note that for all topologies, maximum transmission power is sufficient to reach maximum network capacity. Our results show that the topology has a significant impact on capacity and energy consumption; however, all of the Pareto-Front curves show similar behavior. For example, topology '*Random 4*' provides the maximum capacity with an energy consumption of 18% less than topology '*Random 7*'.

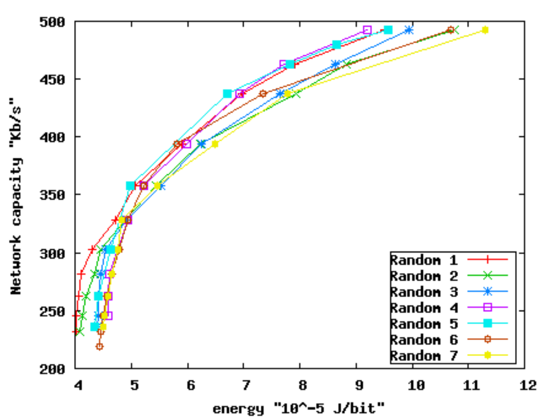


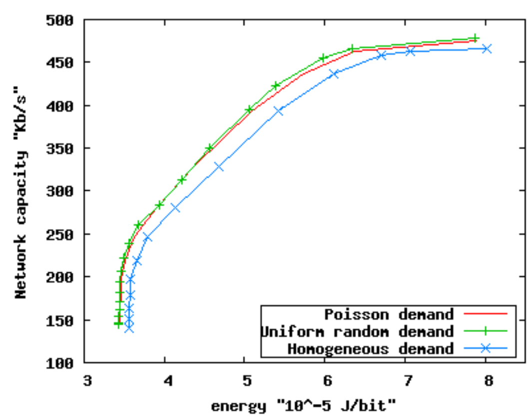
Fig. 9. Capacity and energy tradeoff with multi-rate transmission and continuous power control: impact of topology.

2) Impact of the throughput requirement: To examining the impact of the throughput requirement distribution on the energy-capacity tradeoff, we compare the following distributions with the same mean value [3].

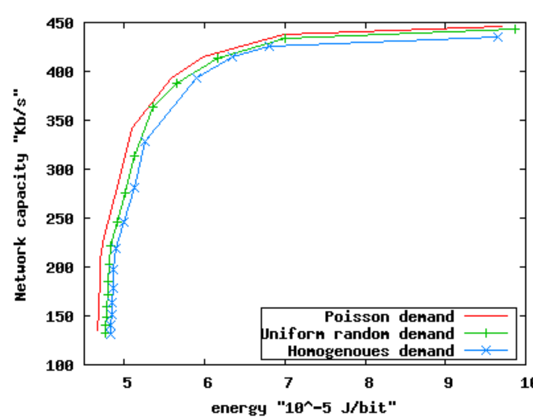
[3]The optimization problem being linear and the results being reported as J/b and Kn/s, the actual value of the mean requirement has no impact on the numerical results. For our simulations, it was set to 2.

- Homogeneous distribution: all MRs have the same weight
- Uniform random distribution: weights are distributed uniformly and independently
- Poisson random distribution: weights are distributed according to a Poisson distribution

The results are reported in Fig. 11, which illustrates the energy-capacity tradeoff as a function of weight distribution, in the case of grid and random networks. The impact of the throughput requirement on the energy-capacity tradeoff is very low. Actually, the traffic load distribution is not very important; the bottleneck area around the gateway has the most impact on capacity. In addition, the case of a high traffic load concentrated in an area was also studied. Fig. 11(b) showed that the impact of the weight distribution is significant when there is a traffic load concentrated in an area that creates another bottleneck area. Fig. 11(a) shows the impact of the distance between the bottleneck and the gateway: the energy consumption decreases when the bottleneck is near the gateway, while the network capacity is almost the same. Based on this observation, the bottleneck-gateway distance parameter should be taken into consideration in the network planning and design.



(a) Random topology, continuous power control



(b) Grid topology, continuous power control

Fig. 10. Capacity and energy tradeoff with multi-rate transmission and continuous power control: impact of weight distribution.

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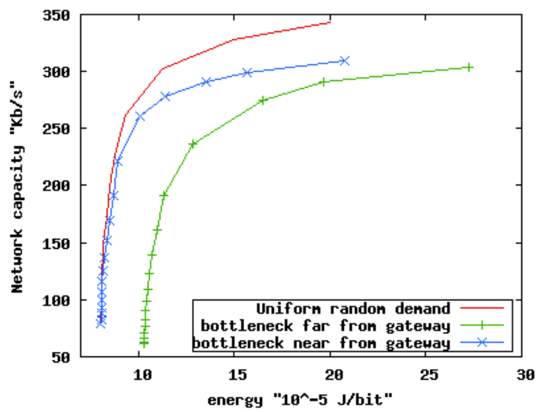
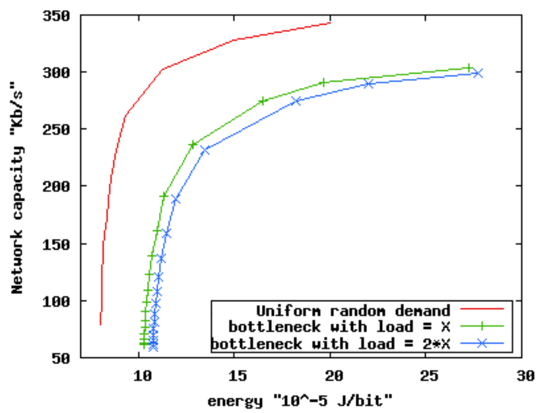


(a) Impact of the distance between the bottleneck and the gateway on the energy-capacity tradeoff



(b) Impact of the magnitude of the bottleneck on the energy-capacity tradeoff

Fig. 11. Impact of bottleneck on energy-capacity tradeoff with MCS3 and continuous power control.

VII. Discussion and Conclusion

A. Discussion

In this section we discuss the main contributions of this paper with respect to other results in the literature. This discussion is divided into two Sections: the first is about our optimization framework presented in Section IV. The second is about network design insights, which can be deduced from our results.

1) Optimization framework: The main contribution of our optimization framework consists in using continuous power control, which allows fine-tuning of transmit power; however, this adds more complexity to the optimization problem. Our framework allows the optimal capacity to be computed under a realistic physical layer, based on SINR interferences, continuous power control, and multi-rate transmissions. One key idea is to model a single logical link as multiple parallel physical links with different radio transmission parameters. This allows us to use a tractable scheduling and routing formulation. By computing a restricted set of decision paths and ISets, column generation enables this problem to be solved within a reasonable time.

Enhancing scalability, to handle a growing amount of nodes, remains a significant challenge in the literature. Currently, we can study networks with 30 nodes using continuous power control and multi-rate transmissions in a reasonable amount of time.

2) Network design guidelines: Our optimization framework allows the offline computation of the optimal system settings of the network. This enables us to derive practical engineering insights and effective benchmarking. This paper focuses on the relationship between energy consumption and network capacity. Our numerical results show that the energy-capacity tradeoff increases with continuous power control (Section V) and with multi-rate transmissions (Section VI).

The advantages of continuous power control are shown in Sections V and VI. Network capacity and energy consumption are optimized by reducing transmit power and interferences. This confirms the results of [5], [6], [8] which show that discrete power control (a set of power levels) improves the spatial reuse and hence improves the throughput. Ours results show that the use of multi-rate transmissions is beneficial for providing highest capacity with low energy consumption. Moreover, we investigate several topologies and weight distributions. We found that the weight distribution has no impact on energy and capacity: alone the congested area around the neighborhood of the gateway influences the energy-capacity tradeoff, which is coherent with previous works on capacity [4], [5], [25].

These results can serve as a guide for the development of protocols which maximize the capacity with efficient energy consumption. For example, a routing strategy and MCS distribution can be derived from our results. Indeed, we show that we can significantly increase the network capacity by allowing the nodes communicate directly with the gateway in the congestion area (around the gateway), using MCS with high throughput (MCS4 and MCS5). For the sake of energy consumption it is more efficient to use multi-hop communications outside of this region, combined with spatial reuse. The implementation and testing of a protocol based on this approach is one of our future goals.

B. Conclusion and perspectives

In this paper, we have addressed the problem of network capacity and energy consumption optimization in WMN. A set of novel linear programming models, using a column generation algorithm, was presented. The later computes a linear relaxation of the routing and scheduling problem with a realistic SINR model and using continuous power control. Since the objective of maximizing the network capacity is often in conflict with the objective of energy minimization, we carried out a thorough study of the tradeoff between them. We investigated the problem of joint resources, MCS, and transmission power allocation, to compute an optimal offline configuration of the network. This work assumed single-channel and single-radio nodes. It is possible to extend our formulation to multi-channel and multi-radio; however, the price is obviously a dramatic increase in complexity. Another challenge is to go beyond the static and offline optimization approach presented in this paper and investigate how to take into account the dynamics of parameters such as throughput demand or channel state.

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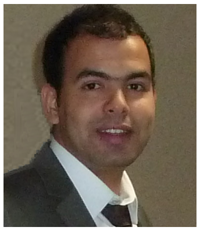

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